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(71) Applicant (for all designated States except US):
KATHOLIEKE UNIVERSITEIT LEUVEN [BE/BE];
Groot Begijnhof 59, B-3000 Leuven (BE).

(72) Inventors; and
(75) Inventors/Applicants (for US only): BERCKMANS,
Daniel, Albert [BE/BE]; Slangenstraat 37, B-3010
Kessel-Lo (BE). AERTS, Jean-Marie [BE/BE]; Koni-
jnenhoekstraat 8, B-3053 Haasrode (BE). VRANKEN,
Erik, Joannes, Matheus [BE/BE]; Molendijkstraat 151,
B-3582 Beringen (BE).

(74) Agent: PRINS, A., W.; Vereenigde, Nieuwe Parklaan 97,
NL-2587 BN The Hague (NL).

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(54) Title: METHOD AND SYSTEM FOR CONTROLLING BIORESPONSE OF LIVING ORGANISMS

(57) Abstract: The present invention describes a method and a system, which allows the prediction as well as the guiding of the
bio-response of living organisms towards a predefined reference bio-response. A further embodiment of the invention is the use of
the method in order to estimate the average weight of animals using an automatic weighing system.

Title: Method and system for controlling bioresponse of living organisms.

Field of the invention

The present invention relates to a method and a system for controlling dynamic bioresponse of living organisms, in particular biomass production of animals, towards a predefined value and/or along a predefined

5   trajectory.

Background of the invention

In the bio-industry a need exists to be able to actively and accurately control the output of bioprocesses, such as the biomass

10   production of an animal, in order to produce output that satisfies consumers' demand. An important bioprocess output is for instance the growth trajectory and final weight of living organisms, e.g. animals. Said growth trajectory and final weight, or more generally biomass production, can be influenced by one or more process inputs, such as feed quantity, quality and

15   frequency (nutritional inputs) and/or temperature, humidity, light intensity and ventilation (micro-environmental inputs). Preferably, the desired bioprocess output is realized at minimum costs, thus with minimum input-effort. From an economic point of view feed intake is an important input to be minimized since it accounts for more then 70% of total production costs

20   (Parkhurst, 1967; Ingelaat, 1997).

One way to control bioprocesses, such as the aforementioned growth or other biomass outputs is by applying model based control theory (Golten and Verwer, 1991; Camacho and Bordons, 1999). This requires the availability of a process model that allows to predict the dynamic response

25   of the process output (the biomass) to one or more process inputs (the before-mentioned nutritional and/or micro-environmental inputs). For implementation in practice, such a process model should be compact and accurate.

In literature many models have been disclosed which describe the growth response of animals in general (Bertalanffi, 1938; Brody, 1945; Emmans, 1981; Kirkwood and Webster, 1984; Moore, 1985; Emmans, 1994) and of broilers in particular (Hurwitz et al., 1978; Timmons and Gates,

5   1988; Fattori et al., 1991; Cooper and Washburn, 1998). These models are basically mechanistic models describing the dynamic response, in particular the growth process, based on physiological and biochemical laws, resulting in complex models, existing of many equations and model parameters (Bruce and Clark, 1979; Oltjen et al., 1986). Such models are excellent for

10   gaining insight, transfer of scientific knowledge and for simulation of processes, but for control purposes in practice they are too complex and too inaccurate (Oltjen et al., 1986).

Beside mechanistic models, also empirical (non-linear) models are found in literature describing growth processes. These models are mainly

15   the result of a non-linear regression analysis applied to growth data (Brody, 1945; Fitzhugh, 1976). The advantages of such models are that they are accurate and have not such a complex structure. However, the models are estimated off-line (after all data are gathered) and usually only take into account the process output (weight as a function of time). Feed intake is not

20   taken into account as a process input. This makes these known models less useful for control purposes.

It is an object of the invention to provide a method for monitoring and control bio-response of living organisms. More particularly it is an object of the invention to use less complex models and modelling techniques

25   to model the dynamic response of a bioprocess output (biomass) to one or more process inputs.

Summary of the invention

The present invention describes a method for monitoring and controlling bio-response of living organisms characterized by the features of claim 1.

The use of a data based on-line modelling technique, based on real-
5   time information, measured dynamically on inputs and outputs of the bioprocess offers the advantage that such models can have a simple structure, yet surprisingly enable accurate prediction of the dynamic behaviour of complex bioprocesses. Thanks to their simple structure, said models can be readily implemented in process control means, at
10   commercially acceptable costs.

In this description on-line modelling at least refers to techniques where a model of the process is identified as the input-output data of the process become available. Synonyms are real-time identification and recursive identification (Ljung, 1987. System Identification: theory for the
15   user, p. 303-304, New Jersey: Prentice Hall). With these modelling techniques the model parameters of a mathematical model structure are estimated, based on on-line measurements of the process inputs and outputs. This parameter estimation can be performed recursively during the process resulting in a dynamic model with time-variant model parameters
20   that can cope with the dynamic behaviour of most bioprocesses (Ljung, 1987; Goodwin and Sin, 1984).

This dynamic model can subsequently be used to estimate and predict the process output several time steps ahead. These predictions can be compared to actual measured output values and a predefined, reference
25   output, based on which comparison a suitable control strategy can be determined, to control the input of the process such as to achieve the predefined output trajectory, preferably with a minimum of input effort.

One way to on-line model the dynamic responses of a bioprocess with time-variant characteristics according to the present invention is by
30   applying recursive linear regression. Such approach offers the advantage

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that, although it is based on a simple model structure, it can cope with non-linear characteristics of processes by estimating the model parameters each time new information is measured on the process. Furthermore the model structure can cope with multiple process inputs and/or multiple process

5   outputs.

The recursive modelling technique according to the invention requires on-line measured input-output information of the process. For instance, when applied to animal growth processes, on-line information regarding animal weight and feed supply has to be made available. From

10   practice systems are known which can measure the required information automatically. However, it is also known that such automatic measurement systems may sometimes yield incorrect measurement values, for instance due to irregular visiting patterns of the animals visiting the measurement equipment. In order to prevent such incorrect measurements from affecting

15   the model accuracy, a method according to the invention is preferably provided with features to evaluate incoming measurements and reject or adapt said measurements in the event inconsistencies are detected. For the evaluation of the measured output data, effective use can be made of the model. For instance, the predicted average output of said model can be used

20   to evaluate the validity of measured output values.

The invention furthermore relates to a system, which adjusts the inputs of a bio-process, in particular animal biomass production, in order to guide the output of the bio-process, e.g. the biomass production, towards a preset reference bio-response using a method according to the invention.

25   This system comprises a means for real-time collecting and storing information on bio-process inputs, for instance feed quantity, and outputs, for instance body weight, a means for generating the predicted bio-process using said information, a means for comparing and determining the variance between the predicted bio-response and the predefined reference

bio-response and means for adjusting the bio-process inputs in relationship to the variance.

Thanks to the compactness of the model according to the invention, said model can be easily implemented on a chip, which chip can be attached
5   to an individual animal, preferably together with one or more appropriate sensors for measuring the animal production inputs and outputs and communication means for communicating with input adjusting means. In this way, the production output or well-being of single animals can be optimally controlled, preferably with a minimum or most efficient use of
10   available inputs, using a modelling technique and model predictive control strategy according to the invention.

Brief description of the drawings and pictures

To explain the invention, exemplary embodiments of a method and
15   system according to the invention will hereinafter be described with reference to the accompanying drawings, wherein:

Fig. 1 represents a block diagram illustrating the general structure of an adaptive control scheme according to the invention;

Fig. 2 shows an example of the rectangular window approach;
20   Fig. 3 shows a scheme of the different calculation blocks and the coupling between growth control and monitoring, wherein the respective blocks represent:

Block 1: the recursive parameter estimation;

Block 2: Calculation of the step response $\gamma(t)$;
25   Block 3: Calculation of the step response matrix G;

Block 4: Calculation of K;

Block 5: Calculation of the free response f;

Block 6: Calculation of the control input for t+1;

Block 7: Prediction of process output k steps ahead;

Block 8: Determination of lower threshold and upper threshold; and

Block 9: Estimation of average weight of group animals.

Fig. 4 shows the growth trajectory (average body weight as a function of time) of ad libitum fed chickens, as compared to a growth trajectory which was controlled towards a predefined reference weight trajectory with a method according to the present invention; and

Fig. 5 represents a table of suitable input-output combinations, for various bioprocesses, and available suitable measurement techniques.

Detailed description of the invention

Figure 1 shows schematically a system 1 according to the invention, for monitoring and controlling bio-response of a bio-process 3, using an on-line data based modelling technique and real-time information measured on selected inputs $u_i(t)$ and outputs $y(t)$ of the bio-process 3.

In this description the term bio-process 3 should be understood to comprise biomass production activity of living organisms, in particular animals. The output $y(t)$ of the bioprocess 3 may include biomass production (e.g. body weight, egg mass, milk yield), biomass composition (e.g. meat/fat ratio, meat quality, milk quality, carcass composition) and waste production (like manure production, manure composition, ammonia emission).

The inputs $u_i(t)$ of the bioprocess 3 include factors which can affect the course of the bio-process 3 and which therefore constitute suitable instruments to control the outputs $y(t)$ of the bio-process 3 towards a predefined, desired value, preferably along a predefined reference trajectory. The inputs $u_i(t)$ can for example include nutritional inputs such as the feed quantity, feed composition, feeding strategy (e.g. feed frequency), water supply and/or micro-environmental inputs like temperature, humidity, ventilation and light intensity.

The system 1 comprises input control means 5 for measuring and adjusting one or more selected inputs $u_i(t)$ to the bio-process 3, output measurement means 7 for measuring one or more selected outputs $y(t)$ of the bio-process 3. The system 1 furthermore comprises a computing means

5   10, connected to said input control means 5 and said output measurement means 7. The computing means 10 is provided with an algorithm 14, for online generating a dynamic model 15 of the bio-process 3, based on real-time measurements of the or each input $u_i(t)$ and output $y(t)$ received from said input control means 5 and output measurement means 7. An example of a

10   suitable on-line modelling algorithm will be discussed in more detail below.

The computing means 10 furthermore comprises an algorithm 16, for calculating a control action 18, which indicates how the or each input $u_i(t)$ should be adjusted in order to obtain the desired output $y(t)$. The calculation of the control action 18 is based on predicted process output

15   values generated by the model 15, which are compared to actual process output values measured by the measurement means 7 and a predefined, desired bio-response 20. Based on the comparison, the control algorithm 16 will calculate how the input $u_i(t)$ should be adjusted in order to obtain the desired output $y(t)$. The algorithm offers the possibility of optimising the

20   inputs $u_i(t)$, so that a desired output $y(t)$ can be achieved with minimum input effort. Underlying mathematical equations for calculating the control action 18 will be discussed in more detail below. The calculated control action 18 is subsequently used to operate the input control means 5, resulting in an adjustment of the input $u_i(t)$.

25   The predefined bio-response 20 can be a desired end value and/or a trajectory leading up to said end value. Said predefined bio-response may be adapted during the process 3. To that end, the computing means 10 can be provided with suitable entry means (not shown), such as a keyboard.

The inputs $u_i(t)$ and outputs $y(t)$ can be measured with suitable

30   sensors. The selected inputs will depend on the output to be controlled.

Subsequently, the techniques for measuring said inputs and outputs may differ. Figure 5 represents a table giving an overview of suitable control inputs $u_i(t)$, as well as suitable measurement techniques for different animal species and different bioprocess outputs to be controlled (e.g. body weight,
5 milk yield, egg mass).

Depending on the field of application, the measured in- and outputs can be averaged values, representing an average quantity of a group of animals. However the in- and outputs can also be measured on individual animals, in which case individual models can be generated for every single
10 animal. In that case, each animal can for instance be provided with a chip and suitable measurement sensor, which can be attached to for instance an ear tag or collar. The chip may contain the algorithms 14 and 16 to estimate the model and generate an appropriate control strategy. Furthermore a receiver and transmitter can be provided for communication with input
15 control means 5, for instance a feeding apparatus.

Modelling of biomass production to production inputs

In the following the mathematical technique for modelling the
20 bioprocess 3 will be described in more detail. This modelling technique estimates model parameters $\theta_i(t)$ of a mathematical model structure, based on on-line measurements of one or more inputs $u_i(t)$ and outputs $y(t)$ of the bioprocess 3 to be controlled. The estimation of the model parameters $\theta_i(t)$ is performed recursively during the process resulting in a dynamic model 15
25 with time-variant model parameters that can cope with the dynamic behaviour of animal biomass production. Typically such a model comprises following elements:

a mathematical relation between a selected output $y(t)$ and input $u_i(t)$ of the bioprocess 3, denoted as:
30

$$y(t) = \theta_1(t) + \theta_2(t)u_1(t) + \dots + \theta_{N+1}u_N \qquad (1)$$

with $\theta_1(t)$, $\theta_2(t)$, ..., $\theta_{N+1}(t)$ representing the model parameters estimated at time t. Note that this relation may be non-linear and may have several inputs ($u_i(t)$). In matrix notation equation (1) can be written as:

$$y(t) = \underline{a}(t)\underline{x}(t) \qquad (2)$$

with $\underline{a}(t) = \begin{bmatrix} \theta_1(t) & \theta_2(t) & \dots & \theta_{N+1}(t) \end{bmatrix}$; $\underline{x}(t) = \begin{bmatrix} 1 & u_1(t) & \dots & u_N(t) \end{bmatrix}^T$,

Next, the parameters $\theta_i(t)$ of equation (1) are estimated recursively using a moving rectangular window approach (illustrated in figure 2) with overlapping intervals of length S. On every time instant t, the parameters $\theta_i(t)$ are estimated, based on measured input and output information during a time window of S samples. The estimation comprises following steps at each recursion (Young, 1984):

receipt of new data at t-th instant

$$\underline{\hat{a}}'(t) = \underline{\hat{a}}(t-1) - P(t-1)\underline{x}(t)\left(\underline{x}(t)^T P(t-1)\underline{x}(t)+1\right)^{-1}\left(\underline{x}(t)^T \underline{a}(t-1) - y(t)\right) \qquad (3)$$

$$P'(t) = P(t-1) - P(t-1)\underline{x}(t)\left(\underline{x}(t)^T P(t-1)\underline{x}(t)+1\right)^{-1}\underline{x}(t)^T P(t-1) \qquad (4)$$

removal of data received at (t-S)-th interval.

$$\underline{\hat{a}}(t) = \underline{\hat{a}}'(t) - P'(t)\underline{x}(t-S)\left(\underline{x}(t-S)^T P'(t)\underline{x}(t-S)-1\right)^{-1}\left(\underline{x}(t-S)^T \underline{a}'(t) - y(t-S)\right) \qquad (5)$$

$$P(t) = P'(t) - P'(t)\underline{x}(t-S)\left(\underline{x}(t-S)^T P'(t)\underline{x}(t-S)-1\right)^{-1}\underline{x}(t-S)^T P'(t) \qquad (6)$$

where $\underline{\hat{a}}(t)$ is the estimate of the parameter vector $\underline{a}(t)$ at time t; $\underline{x}(t)$ is defined as in equation (2); S is the size of the rectangular window; P is a square matrix which is initialised at

$$P = \begin{bmatrix} 10^4 & 0 & ... & 0 \\ 0 & 10^4 & ... & 0 \\ ... & ... & ... & ... \\ 0 & 0 & ... & 10^4 \end{bmatrix}$$

Predictions of the biomass output are generated in a recursive way. On each time instant t the parameters $\theta_i(t)$ of equation (1) are estimated based on the measured process output and inputs in a time window of S time units (from time unit t-S+1 until time unit t). In a next step, the process output is predicted F steps ahead (time unit t+F) by using equation (1) with $u_i(t+F)$, wherein F will be called the prediction horizon. On time unit t+1 the procedure is repeated. So, based on the measured information in a time window ranging from t-S+2 until t+1, the model parameters $\theta_i(t+1)$ are estimated and biomass production is predicted F days ahead (time unit t+1+F) by applying the input $u_i(t+1+F)$ to the estimated model. In this way the process output (biomass production) is predicted at each time instant on the basis of a limited window of actual and past data.

The optimum values for the window length S and prediction horizon F will be different for every process to be modelled. The optimum values can for example be determined by evaluating the accuracy of the model predictions for various combinations of window length S and prediction horizon F and by selecting the combination for which the prediction error remains below a specified, acceptable value, for instance below 5%.

Based on the predictions of the recursive modelling technique, algorithms can be developed to control the biomass trajectory.

Model-based control of the biomass trajectory

In order to obtain a suitable control algorithm, model predictive control (MPC) makes use of an objective function J. The general aim is that

the future process output (y(t)) on the considered horizon F should follow a

determined reference signal (r(t)) and, at the same time, the control effort

(Δu) necessary for doing so should be penalized. The general expression for

such objective function is (Camacho and Bordons, 1999):

5 $$J(N_1, N_2, N_u) = \sum_{F=N_1}^{N_2} \delta(F)[\hat{y}(t+F \mid t) - r(t+F)]^2 + \sum_{F=1}^{N_u} \lambda(F)[\Delta u(t+F-1)]^2 \qquad (7)$$

where N_1 is the minimum cost horizon; N_2 is the maximum cost

horizon; N_u is the control horizon, $\hat{y}(t+F \mid t)$ is the predicted value of the

process output y on time instant t, F time steps ahead; r(t+F) is the value of

the reference trajectory on time instant t+F; Δu(t+F-1) is the change of the

10   control input on time instant t+F-1; δ(j), λ(j) are weighing coefficients.

The following examples will further explain the invention.

Example 1: Control of the weight trajectory of growing chickens

5800 chickens (Ross 308, mixed) were divided into two groups of

15   2900 animals each. One group was fed ad libitum, while the amount of feed

supplied to the animals of the second group was controlled, using the data

based on-line modelling technique according to the present invention, in

order to guide the weight trajectory towards the predefined reference

growth trajectory. Being able to guide the weight trajectory offers the

20   possibility to select a trajectory that offers optimum results for specific,

predetermined criteria. For instance one could select a trajectory that leads

to maximum growth in a minimum time frame or with minimum input

(feed). One could also choose to maximise the animals well being and thus

minimise production loss. Other criteria to be optimised can be for instance

25   a minimum of manure production or a favourable meat/fat ratio. Also, by

controlling the input, waste of input can be avoided.

The weight of the animals was determined using an automatic

weighing platform (Fancom 747 bird weighing system) with a diameter of

0.24 m. Water and food was provided by means of an automatic drinking
feeding system (Roxell). Feed intake and average weight of the animals was
determined on a daily basis. Calculations were performed on a Pentium II
(200 MHz). The method used to model and control the weight trajectory is

5   described in detail below, whereas a block diagram of the model used is
shown in figure 3.

    Figure 4 presents the evolution in time of the average body weight
of the animals in the two experimental groups as compared to the
predefined reference weight trajectory. The body weight of the animals in

10   the ad libitum fed group increased clearly faster than in the preset growth
trajectory, while the weight trajectory of the controlled group coincided with
the reference trajectory.

    In order to model the growth response to feed supply, cumulative
feed intake was chosen as input instead of the daily feed intake, since the

15   trajectory of weight as a function of cumulative feed intake is much more
damped (smooth) than the trajectory of weight as a function of feed intake
(Fitzhugh, 1976). In the reported research, it is assumed that the relation
between cumulative feed intake and weight, which is non-linear (Brody,
1945; Fitzhugh, 1976; Parks, 1982), can be described by recursive linear

20   relations between both variables. So, on each discrete time instant k the
following linear relation can be written (see block 1, fig. 3):

$$\hat{W}(t) = \theta_1(t) + \theta_2(t)CF(t) \tag{1}$$

    where W(t) is the measured weight (kg) of the animals at time t;

25   CF(t) is the measured cumulative feed intake in kg at time t; $\theta_1(t)$(kg) and
$\theta_2(t)$(kg/kg) are the model parameters estimated at time t (days). The
parameter $\theta_2(t)$ more specifically, is the feed efficiency at time t (defined as
change of bird weight per change of feed intake). The parameter $\theta_1(t)$ at the

start of the experiment, day 1, equals the body weight of the day-old chick. In matrix notation this can be written as:

$$\hat{W}(t) = \underline{a}(t)\underline{x}(t) \tag{2}$$

with $\underline{a}(t) = [\theta_1(t) \quad \theta_2(t)]$; $\underline{x}(t) = [1 \quad CF(t)]^T$, the superscript T meaning the transpose of a matrix.

At each recursion, using a moving rectangular window approach as described above, the estimation consists of the following steps: receipt of new data at t-th instant

$$\underline{\hat{a}}'(t) = \underline{\hat{a}}(t-1) - P(t-1)\underline{x}(t)\left(\underline{x}(t)^T P(t-1)\underline{x}(t) + 1\right)^{-1}\left(\underline{x}(t)^T \underline{a}(t-1) - w(t)\right) \tag{3}$$

$$P'(t) = P(t-1) - P(t-1)\underline{x}(t)\left(\underline{x}(t)^T P(t-1)\underline{x}(t) + 1\right)^{-1}\underline{x}(t)^T P(t-1) \tag{4}$$

removal of data received at (t-S)-th interval.

$$\underline{\hat{a}}(t) = \underline{\hat{a}}'(t) - P'(t)\underline{x}(t-S)\left(\underline{x}(t-S)^T P'(t)\underline{x}(t-S) - 1\right)^{-1}\left(\underline{x}(t-S)^T \underline{a}'(t) - w(t-S)\right) \tag{5}$$

$$P(t) = P'(t) - P'(t)\underline{x}(t-S)\left(\underline{x}(t-S)^T P'(t)\underline{x}(t-S) - 1\right)^{-1}\underline{x}(t-S)^T P'(t) \tag{6}$$

where $\underline{\hat{a}}(t)$ is the estimate of the parameter vector $\underline{a}(t)$ at time t and in the given example $\underline{\hat{a}}(t) = [40 \ 0.8]$ at t = 0; $\underline{x}(t)$ is defined as in equation (2); P is a square matrix which is initialized at $[10^4 \ 0; 0 \ 10^4]$; S is the size of the rectangular window.

On each time instant (day) t the parameters $\theta1(k)$ and $\theta2(k)$ of equation (1) are estimated based on the measured values of weight and cumulative feed intake during a time window of S=5 days (from day t-S+1 until day t). In a next step, the weight is predicted F= 4 steps ahead (day t+F) by using equation (1) with CF(t+F). On day t+1 the procedure is repeated.

The window length S=5 and prediction horizon F=4 were determined by applying the recursive estimation algorithm with different window sizes, ranging from three to seven days and different prediction

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horizons, ranging from one to seven days. As a result, for each data set 35 (5 x 7) combinations of window size and prediction horizon were used to model the growth response. It could be demonstrated that the prediction error stayed below 5 % when a window size S of 5 days was used and the
5   prediction horizon did not exceed 4 days.

Based on abovementioned predictions a control algorithm was developed to control the growth trajectory and to monitor the time course of the animals' weight, using before-mentioned objective function:

$$J(N_1, N_2, N_u) = \sum_{F=N_1}^{N_2} \delta(F)[\hat{y}(t+F|t) - r(t+F)]^2 + \sum_{F=1}^{N_u} \lambda(F)[\Delta u(t+F-1)]^2 \qquad (7)$$

10   where N_1 is the minimum cost horizon; N_2 is the maximum cost horizon; N_u is the control horizon, $\hat{y}(t+F|t)$ is the predicted value of the process output y on time instant t, F time steps ahead; r(t+F) is the value of the reference trajectory on time instant t+F; $\Delta u(t+F-1)$ is the change of the control input on time instant t+F-1; $\delta(j)$, $\lambda(j)$ are weighing coefficients.

15   For the present example the objective function can be more specifically written as:

$$J(1,4,4) = \sum_{j=1}^{4} [\hat{W}(t+F|t) - r(t+F)]^2 + \sum_{j=1}^{4} \lambda(F)[\Delta CF(t+F-1)]^2 \qquad (8)$$

where $\hat{W}(t+F|t)$ is the predicted weight of the group animals and CF is the cumulative feed supply.

20   Typically for MPC (model predictive control) is to separate the process response into a free and a forced response. The free response corresponds to the evolution of the process due to its present state, while the forced response is due to the future control moves. For the considered process, the weight can be predicted 1 step ahead using the following
25   equation:

$$\hat{W}(t+1) = W(t)(1-\xi) + \gamma(t)\Delta CF(t+1) \qquad (9)$$

where $W(t)(1-\xi)$ is the free response and $\gamma(t)\Delta CF(t+1)$ is the forced

response. Based on experiments, the value of the parameter ξ was

estimated. The value of ξ ranges between 0.04 and 0.1. The parameter $\gamma(t)$

can be expressed as function of $\theta_2(t)$ as (see block 2, fig. 3):

5   $$\gamma(t) \approx \theta_2(t) + \frac{\xi w(t-1)}{\Delta CF(t)} \tag{10}$$

For predictions up to 4 days (F = 4), the weight can be predicted as

follows:

$$\hat{W}(t+F) = W(t)(1 - F\xi) + \sum_{F=1}^{4} \gamma(t)\Delta CF(t+F) \tag{11}$$

In matrix notation this can be written as:

10   $$\begin{bmatrix} \hat{W}(t+1) \\ \hat{W}(t+2) \\ \hat{W}(t+3) \\ \hat{W}(t+4) \end{bmatrix} = \begin{bmatrix} w(t)(1-\delta) \\ w(t)(1-2\delta) \\ w(t)(1-3\delta) \\ w(t)(1-4\delta) \end{bmatrix} + \begin{bmatrix} \gamma(t) & 0 & 0 & 0 \\ \gamma(y) & \gamma(t) & 0 & 0 \\ \gamma(t) & \gamma(t) & \gamma(t) & 0 \\ \gamma(t) & \gamma(t) & \gamma(t) & \gamma(t) \end{bmatrix} \begin{bmatrix} \Delta CF(t+1) \\ \Delta CF(t+2) \\ \Delta CF(t+3) \\ \Delta CF(t+4) \end{bmatrix} \tag{12}$$

or more compact as

$$\hat{W} = f + G\Delta CF \tag{13}$$

where f is the free response (block 5, fig. 3):

$$f = \begin{bmatrix} W(t)(1-\delta) \\ W(t)(1-2\delta) \\ W(t)(1-3\delta) \\ W(t)(1-4\delta) \end{bmatrix} \tag{14}$$

15   and G is the step response matrix (block 3, fig. 3).

$$G = \begin{bmatrix} \gamma(t) & 0 & 0 & 0 \\ \gamma(t) & \gamma(t) & 0 & 0 \\ \gamma(t) & \gamma(t) & \gamma(t) & 0 \\ \gamma(t) & \gamma(t) & \gamma(t) & \gamma(t) \end{bmatrix} \tag{15}$$

By substituting equation (13) into the objective function J

(equation (8)) and making the gradient of J equal to zero (under assumption

20   that there are no constraints on the control signal) this leads to

$$CF = \left(G^T G + \lambda I\right)^{-1} G^T (r - f) \qquad (16)$$

Predictive control uses the receding horizon principle. This means that after computation of the optimal control sequence, only the first control will be implemented, subsequently the horizon is shifted one sample and the optimisation is restarted with new information of the measurements. So, the actual control signal that is sent to the process is the first element of the vector CF and is given by (block 6, fig. 3):

$$\Delta CF(t + 1) = K(r - f) \qquad (17)$$

where $\Delta CF(t+1)$ is the feed that has to be supplied to the animals on time t and that is available until time $t+1$; K is the first row of matrix $\left(G^T G + \lambda I\right)^{-1} G^T$ (block 4, fig. 3).

From research it is known that automatic weighing of chickens may yield different results than when weighing manually. This difference is especially encountered near the end of the production period. The difference is explained (Blokhuis, et al., 1988), by assuming that the weighing system is less visited by heavier birds at the end of the production period. This is confirmed by experience of Klein Wolterink, et al., (1989). In the present example, this problem was solved in the following way.

The on-line estimated relation between the cumulative feed supply CF and the weight W of the animals was used as a basis for optimising the estimation of the average weight of the group animals. Each time instant t the weight can be predicted one step ahead by using the following equation (block 7, fig. 3)

$$\hat{W}(t + 1) = \theta_1(t) + \theta_2(t) CF(t + 1) \qquad (18)$$

where θ1(t) and θ2(t) are the recursive estimated model parameters as described previously (equation 3-6); CF(t+1) is the cumulative feed supply CF(t) plus the calculated control input ΔCF(t+1).

Based on the predicted weight $\hat{W}(t+1)$, lower and upper threshold

5   values LT(t) and UT(t) can be calculated (block 8, fig. 3):

$$LT(t+1) = \hat{W}(t+1) - \psi_L \hat{W}(t+1) \tag{19}$$

$$UT(t+1) = \hat{W}(t+1) + \psi_U \hat{W}(t+1) \tag{20}$$

10

wherein values for ψ_L range between 0.3 and 0.15 and values for ψ_U range between 0.3 and 0.4. These values have been determined, based on experimental data.

These threshold values are used to accept (or reject) the on-line

15   measured weight values w. Since the distribution of the accepted values is biased (especially during the second half of the production period), the estimation of the average weight of the group is not based on the simple average, but on a corrected average. In order to calculate the corrected average, the accepted measured weight values w are divided into n equal

20   classes.

For $cl = 1 \rightarrow n, w = w_{cl} \Leftrightarrow w \in [LT + (cl-1).CW, LT + cl.CW\rangle$

The width of these classes, CW, is calculated as (block 9, fig. 3)

25

$$CW(t+1) = \frac{(UT(t+1) - LT(t+1))}{n} \tag{21}$$

Due to the fact that the lighter animals visit the weighing platform more frequently during the second half of the production period, the

30   distribution is not normal (in statistical terms). In order to normalize the

distribution, the weights in each class are averaged and multiplied by a weighing factor wf. In case that n = 10, the used weighing factors are:

wf1 = wf10 = 0.006

wf2 = wf9 = 0.026

5   wf3 = wf8 = 0.077

wf4 = wf7 = 0.165

wf5 = wf6 = 0.226

The average weight of the group animals is calculated by using the following equation:

10

$$W(t+1) = \frac{\sum_{cl=1}^{n} w_{cl} \cdot wf_{cl}}{\sum_{cl=1}^{n} wf_{cl}} \tag{22}$$

where w_{cl} is the average weight of class cl; and wf_{cl} is the weighing factor wf applied to class cl.

15   In contrast with the available algorithms for estimation of animals' weights with an automatic weighing platform, the method described here, does not need a priori knowledge, but is only based on measured information of the process.

In Figure 3 a scheme of the previously described calculations and
20   the coupling between controlling and monitoring of growth is shown.

Example 2: Control of the growth of pigs

The method using the data based on-line modelling technique can
25   also be applied to monitor and control the weight trajectory of growing pigs. The production inputs to be used are preferably selected out of the group comprising feed supply, feed composition and temperature. The production output parameter can either be the average pig weight or the individual pig

weight. There are several methods to accurately measure the individual weight of pigs in a stable, in a preferred embodiment this is done using Video Imaging.

5   Example 3: Control of the growth of fish
          The method using the data based on-line modelling technique can also be applied to monitor and control the weight trajectory of growing fish. The production input or inputs to be used are preferably selected out of the group comprising feed supply, feeding frequency and water temperature.
10   The preferred production output parameter is the average body weight of the fish. There are several methods to accurately measure the average weight of fish swimming in a tank, in a preferred embodiment this is done using Video Imaging.

15   Example 4: Control of the growth of Bovine animals
          The method using the data based on-line modelling technique can also be applied to monitor and control the weight trajectory of growing bovines. The production inputs to be used are preferably selected out of the group comprising feed supply and feed composition, in a more preferred
20   embodiment the production inputs used are concentrate and roughage supply. The preferred production output parameter is the individual body weight of the bovines. There are several methods to accurately measure the individual weight of bovines, in a preferred embodiment this is done using a Weighing platform.
25

          Example 5: Control of the milk production of lactating cows
          The method using the data based on-line modelling technique can also be applied to monitor and control the milk production of lactating cows. The production inputs to be used are preferably selected out of the group comprising feed supply and feed composition, in a more preferred
30   comprising feed supply and feed composition, in a more preferred

embodiment the production inputs used are concentrate and roughage
supply. The preferred production output parameter is the cumulative milk
production of the bovines. There are several methods to accurately measure
the milk production, in a preferred embodiment this is done using an

5   electronic milk yield sensor, f;ex; Delaval milk meter MM25.

Example 6: Control of the egg production of laying hens

The method using the data based on-line modelling technique can
also be applied to monitor and control the egg production of laying hens. The

10   production inputs to be used are preferably selected out of the group
comprising feed supply, feed composition, temperature and light intensity.
The preferred production output parameter is the cumulative egg mass
production. There are several methods to accurately measure the egg mass
production, in a preferred embodiment this is done using an electronic egg

15   counter, f;ex; Fancom IR.10 egg counter.

Example 7: Control of protein and fat growth

By applying the data based modelling technique, it is also possible
to monitor and control the protein and fat growth of animals (e.g. broilers,

20   pigs). Based on measured data of animal weight, feed (energy) intake and
estimated heat loss, it can be calculated how much protein and fat an
animal is gaining per unit of time. The considered process outputs are
protein and fat gain per time unit, the process inputs to be used are feed
quantity and feed composition (quality). For the measurement of feed supply

25   and animal weight commercial systems are available. Heat loss of animals
can be estimated based on measurement of air temperature, air velocity, air
humidity, radiant temperature of the environment and surface temperature
of the animal.

The invention is by no means limited to the examples given in the description and the drawings. Many variations thereto are possible and understood to fall within the framework of the invention.

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CLAIMS

1.   Method for monitoring and controlling bio-response of living organisms, using a data based on-line modelling technique and real-time information on bioprocess inputs and outputs.

2.   Method according to claim 1 wherein the bio-response of living
organisms comprises animal production of biomass and the real-time information on the bio-process inputs comprises one or a selection of inputs from the following group of animal production inputs: nutritional inputs, such as feed quantity, feed composition, feeding strategy and/or micro-environmental inputs, such as temperature, humidity, ventilation, light
intensity.

3.   Method according to claim 1 or 2 wherein the real-time information on the bio-process outputs comprises one or a selection of outputs from the following group of animal production outputs: biomass production such as animal weight, egg mass, milk yield and/or biomass composition, such as
meat/fat ratio, meat quality, milk quality, carcass composition and/or waste production, such as manure production, manure composition, ammonia emission.

4.   Method according to claims 2 or 3 for the monitoring and control of the body weight trajectory of animals, using real-time information on
animal production inputs and outputs.

5.   Method according to any one of the claims 2-4 wherein the real-time information on animal production inputs consists of data on feed uptake.

6.   Method according to any one of the claims 2-5 wherein the real-
time information on animal production outputs consists of animal weight.

7.   Method for controlling animal well-being by the steps of:

-       predicting a future difference between a desired animal status and a predicted animal status using an adaptive model;

-       changing input parameters to said animal based on said model for minimising said future difference.

5   8.   Use of a method according to any one of the claims 2 to 7 for the adjustment of one or more animal production inputs in order to guide one or more monitored animal production outputs towards a desired output trajectory.

9.   Use of a method according to any one of the claims 2 to 7 for

10   predicting future animal production output of an individual animal or a group of animals.

10.   Use of a method according to any one of the claims 2 to 7 for determining the average body weight of a group of animals.

11   Use of a method according to any one of the claims 8-10, wherein

15   the animals are birds, fish or mammals.

12.   Use of a method according to claim 11, wherein an automatic weighing system is used for on-line measuring of the animal production output, in particular the body weight.

13.   Use of a method according to claim 12, wherein a bias due to more

20   frequent visit of the weighing system by lighter animals than by heavier animals is corrected by comparing the measured average weight with the predicted average weight.

14.   Use of a method according to any one of the claims 11-13, wherein video imaging techniques are used for on-line measuring of the animal

25   production output, in particular the body weight.

15.   Use of an on-line modelling technique based on estimators for controlling bio-response of animals.

16.   System for adjusting the bio-process inputs in order to guide the bio-response of living organisms towards a preset reference bio-response

30   using a method according to claim 1 and comprising a means for real-time

collecting and storing information on bio-process inputs and outputs, a means for generating the predicted bio-process using said information, a means for comparing and determining the variance between the predicted bio-response and the predefined reference bio-response and means for

5   adjusting the bio-process inputs in relationship to the variance.

17.   System for adjusting the animal production inputs in order to guide the weight trajectory of animals towards a preset reference weight trajectory using a method according to any of the claims 2 to 7 and comprising a means for real-time collecting and storing information on

10   animal production inputs and outputs, a means for generating the predicted weight trajectory using said information, a means for comparing and determining the variance between the predicted weight trajectory and the predefined reference weight trajectory and means for adjusting the animal production inputs in relationship to the variance.

15   18.   System according to claim 17, wherein the means for on-line modelling, and preferably the means for generating a control action based on said on-line model are contained on a chip, for attachment to an animal, together with one or more measurement means for measuring the animal production inputs and outputs and communication means, for

20   communicating the on-line model and/or the generated control action from the chip to means, with which the animal production inputs can be adjusted.
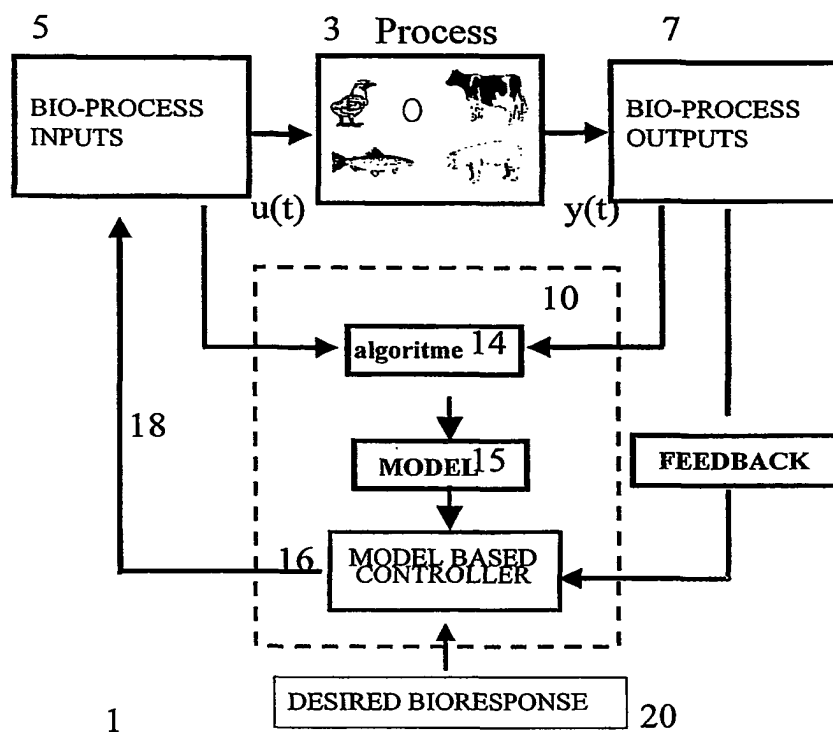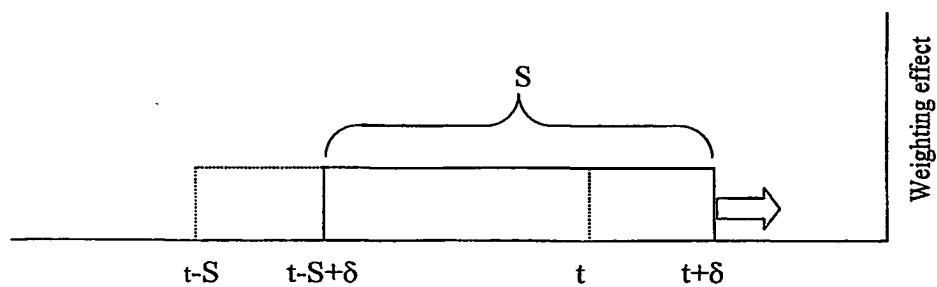
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Fig. 1

Fig. 2